Paper ID: CDC00-INV2303

Control and Random Searching with Multiple Robots

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ABSTRACT

This paper presents the work of several ongoing studies to determine the effectiveness of multiple small robotic vehicles for performing mine field clearance, and the related problem of clearing unexploded ordnance from areas of interest. Many issues are implied in this opening sentence. Not the least of these is knowing, out the many items cluttering a battlefield, which ones need to be cleared. There is the problem of transiting through dangerous areas with the threat of detonation, the difficulties of open field navigation and rough terrain, and the dangerous task of picking up unexploded charges. Current technology employs brute force, is often overt, or the use of human hands - with the potential for loss of life and / or limb.

It is of interest then, to explore whether improvements in safety and performance can be made using small smart machines that have the capability of transiting an open area, obstacle avoidance, and picking up an piece of ordnance, or placing a charge that could be detonated upon command.

Results given in this paper includes the performance of clearance operations with behavior based robots in *random search*. This is where the formations are random, allowing for low cost controllers. Included are the effects of the use of multiple vehicles, the influence of various levels of detection probability, and some estimation of the losses suffered under a given probability that detonation will occur upon ordnance recovery.

INTRODUCTION

The Navy's Explosive Ordnance Disposal (EOD) research and development department has recently been active in the pursuit of small robots - a Basic Unexploded Ordnance Gathering System (BUGS) , as an aid to EOD technicians who are required to enter the battlefield , or test firing range, to clear improved conventional munitions(ICM) [1]. The munitions do not all detonate upon delivery leaving about five percent in a dangerous state. Two methods of clearance are to pick up the offending objects and place hem on a pile for later disposal, or to simply blow them up in place. The pick up and carry away scenario is the subject of this study. We will discuss the clearance performance of multiple robots in performing random search.

Since any field of interest will also be littered with obstacles, reliable obstacle avoidance methods are essential, and target detection sensor(s) are integral to every concept. Additionally, candidate robots must have a reliable capability to pick up the selected object and return to the designated pile point.

RANDOM SEARCH

Given a purely random search for unknown targets within an area A, using a perfect sensor of detection radius, *r*, traveling at speed *U*, we may assume that the probability of detection is proportional to the mean target density, $\bar{n}(t)/A$, times the area sweep rate [2]. With an imperfect sensor where the probability of detection, conditioned on target presence is *p*, we can deduce that the expected rate of target acquisition, $\dot{q}(t)$ is

$$\dot{q}(t) = U(2r)pN(\bar{n}(t)/A).$$

Related to the above, $\bar{n}(t)$ is the average number of targets remaining at time *t*, so that,

$$\bar{n}(t) = -\int_0^t \dot{q}(\tau)d\tau\ ,\ \ \bar{n}(0) = n_0$$

and it is assumed that the remaining are always uniformly distributed - a case unlikely to happen in reality. N is the number of vehicles concurrently involved in the search

Based on the above, the percentage of targets cleared at any time, *t*, during the operation is given by

$$\bar{n}(t)/n_0 = [1 - e^{-\alpha t}]$$

where the characteristic clearance rate is α, and,

$$\alpha = U(2r)pN / A .$$

The analytical consideration is useful in that it shows the importance of the traverse speed, the detection radius and the proportional influence of the number of robots in the field as well as the importance of a high probability of detect, *p*.

Random search using cheap robots has been proposed in [3]. In [4, 5], we show that the random search methodology together with a bounding signal (electronic fence) would be possibly preferred for low cost vehicles (without precise navigation) It was also shown that depending on the placement point used, the coverage by multiple robots may be skewed towards the placement point so that multiple placements are desirable. Homing to a pile point can be accomplished with a placed radio beacon

The requirement of having to perform obstacle avoidance maneuvering while in transit adds time to the search. Results have shown that there is an added time consumed by obstacle avoidance (including avoidance of other vehicles) that reduces the effective speed, so that

$$\hat{U} = \gamma(n_o, N)U$$

where γ, is a reduction factor based on the density of obstacles, time lost to obstacle avoidance and the number of vehicles in the search. The values of $\hat{U} = \gamma(n_0, N)U$ are not known, but could be found from simulation results.

EXHAUSTIVE SEARCH

Studies of the threat to robotic clearance systems indicate that the majority of items will be ferrous in nature so that magnetic detection coils could be used to advantage. On a limited size / cost platform, detection radii not more than approximately 20 cm. are possible. It follows that directed searching is not likely to be better than random searching unless navigational accuracy within centimeters is available.

With the recent developments in differential GPS positioning, accuracy to within standard deviations of less than 2cm. are now claimed [6], which opens the possibility of directed searching to be accomplished with the detection sensors available.

In directed search, the area is swept a constant rate - either in spiral directions, or in a lawnmower pattern. The mean clearance rate is constant at

$$\dot{\bar{q}}(t) = U(2r)pN(\bar{n}(0)/A),$$

$$0 < \bar{n}(t)/\bar{n}(0) < 1$$

until the field is cleared. The expected time for 100% clearance is then,

$$T_o = A/\gamma(n_o, N)U(2r)pN$$

note that the time is inversely proportional to the number of robots, *N*, and *p*, the conditional probability of detection given that the target is within range of the sensor. While this performance indicates that the faster vehicle clears in shorter time, and that increasing the number of working vehicles and the detection radius has a proportional benefit, increasing *N* also reduces γ so that a limit exists to the benefits of increasing to number of vehicles.

TARGETED SEARCH

With the benefit of high precision navigation, it is now possible that an exhaustive search be undertaken by a fleet of robots. Also, if an external means of providing targeting data (expected location of targets to be found and recovered), then, advantage may be taken of the knowledge of the terrain. Freeways may be designed to increase travel speed in certain paths, while slow speed search with obstacle avoidance in unknown sections will produce the knowledge necessary to map building.

At this point, not all segments of area need to be searched, and only those local areas where targets are located need to be searched. In this case, the expected clearance time is

$$T_0 = \bar{d}(UN)^{-1} + \bar{t}(p) + \bar{t}_{oa}(o)$$

in which, $\bar{t}_{oa}(o)$ is the average time spent in obstacle avoidance for n_o obstacles, $\bar{t}(p)$ is the average time spent in locally searching targets with sensor of detection probability, p and $\bar{d}$ is the average distance traveled in pickup and return of all targets.

SIMULATION AND MODELING

Operation of the robot vehicles is complicated by the fact that navigation over rough terrain is required at the same time, obstacle avoidance behaviors have to be running. Behavior based control [7] is used with the exception that arbitration between concurrently running behaviors is simplified to that of switching between discrete modes while algorithmic control laws are used to control the behaviors. An overall canonical automaton for the discrete event control of each vehicle is given in Figure 1.

<u>Robot Navigation</u>

Robot navigation is accomplished with either tracked, walking and wheeled vehicles using a proportional guidance algorithm,

$$\dot{y}_{com}(t) = K(y_{com}(t) - y(t))$$

subject to rate limits from the actuators while the commanded heading is randomized as appropriate and given an additive bias depending on its position relative to the field

<u>BUGS Canonical State Diagram</u>

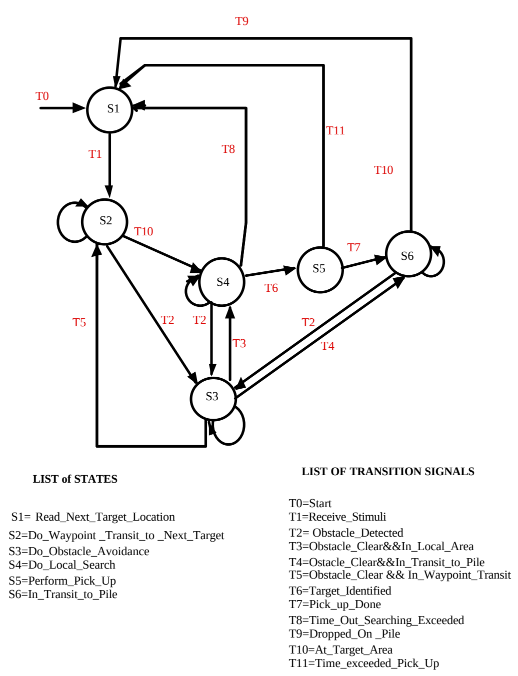

Figure 1 Canonical State Diagram for Robot Mission Control

boundaries. (In practice, an electronic fence could be place around the field boundary, or if a navigation system were available, its position data could be used to set the bias).

$$y_{com}(t) = y_{bias} + y_{random}(t)$$

Wheel speed commands (or tracked vehicle track speeds are derived from the inverse kinematic model of vehicle motion [8]. The navigation implementation requires as a minimum, a compass - preferably without time lags in response. For vehicles that can support a navigation system with DGPS and/or odometry, a guidance law can be included using one of many schemes, the simplest of which is a line of sight guidance [9].

System effectiveness results using a "C" coded program have supplemented a concurrent graphics based simulator development, and now allow for large numbers of Monte Carlo simulations to be conducted in short times.

<u>Obstacle Avoidance Behavior</u>

Obstacle avoidance has been simulated with different algorithms and the simplest has been to stop upon detecion, backup turn right,go forward and check again. This tends to get trapped in complex obstacles but the forward sector avoidance shown in Figure 2 appears to execute quickly and is robust to trapping.

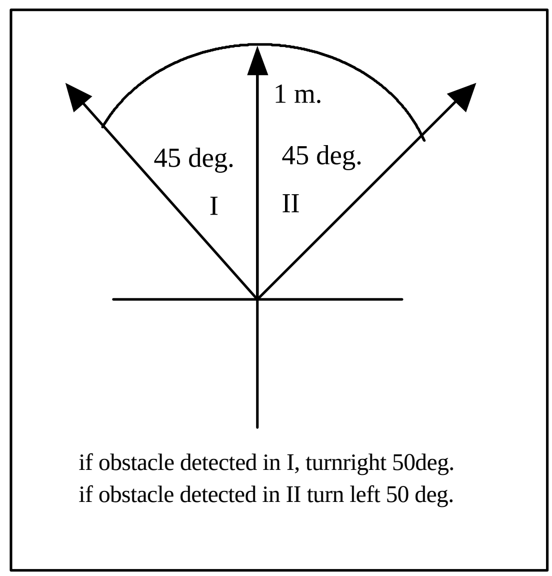

Figure 2 Obstacle Avoidance Scheme Using Forward Looking Sectors

<u>Target Detection and Pickup</u>

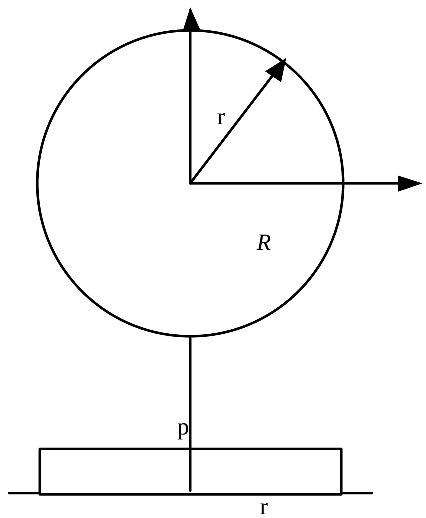

Figure 3 Uniform Target Detection Probability Density Distribution

A successful pick up is assumed if the vehicle can position itself such that the target (x_1,y_2) actually lies within R, the detection circle of radius r.

Since no sensor can be guaranteed to always give a correct signal, the conditional probability, $p\ (r) < 1$, is applied to determine if, given that a target lies inside the region R with the nominal detection radius r from any vehicle, a detect signal is given.

$p\ (r)$ is an appropriate function of radial displacement, although the "cookie cutter" model has been used in this work to date. More representative distributions are easily implemented. A detection signal is declared positive if a uniformly distributed random number, r_n : [0,1] is such that $r_n < p$.

In simulation, if the detection test is invoked each time where (x_1,y_2) lies in R, the effect of multiple applications distorts the apparent success rate. To eliminate this distortion, the test is applied once only after the region R is reached. A perfect pickup has been assumed for these results.

RESULTS

In a scenario that models a uniformly distributed UXO field 60m square, with 72 targets and a similar number of uniformly distributed obstacles, mean and standard deviation of clearance times are found from up to 80 simulations for each particular case. The number 80 was selected based on convergence of the statistics to an invariant result.

In general, the results follow the theoretical exponential clearance performance. Figure 4 indicates a typical path segment, and Figure 5 , the improvement obtained by the use of multiples of vehicles in the same area performing clearance. The results in Figure 5 includes obstacle avoidance and returns to a single pile point in the center of the field.

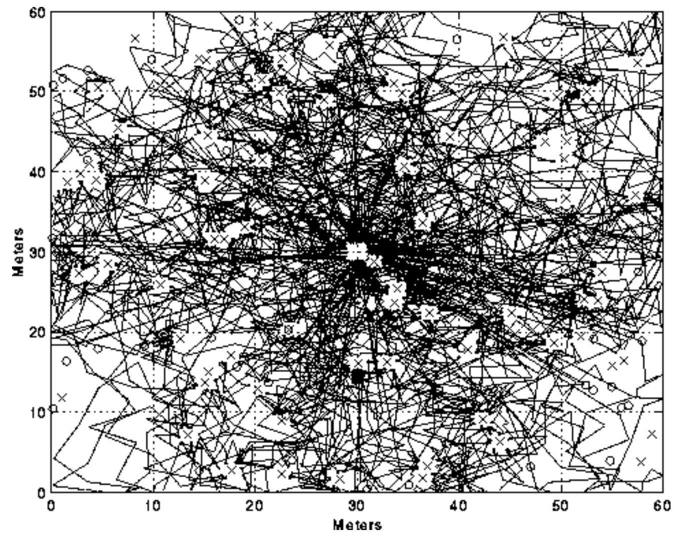

Figure 4 Typical Random Paths For 10 Robots. O Are Targets, + Are Obstacles.

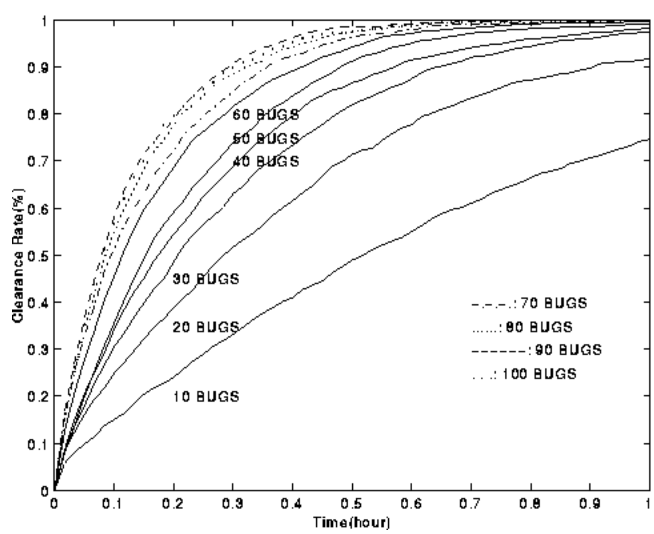

Figure 5 Clearance Performance In Percentage Cleared Versus Time (Hours), [60*60 M Area With 72 Targets And 72 Obstacles, Uniformly Randomly Distributed, Robots With 1m. Detection Radius Traveling At 0.2 M / Sec.], (Electronic Fence Gives Signals To Reflect The Path To The Interior).

It is apparent from Figure 5 that there is a number of robots beyond which further increase of rate is limited. The reason for this lies in the fact that while increasing *N* reduced the characteristic clearance time, increasing *N* also reduces $\gamma(n,N)$ and the effective speed of transit because of increased obstacle avoidance operations.

<u>Sensor Imperfection</u>

The effect of using imperfect sensors for the detection of munitions is illustrated in Figure 6, where for random search, the characteristic clearance time is increased since multiple "looks" at any one target are required to declare detection.

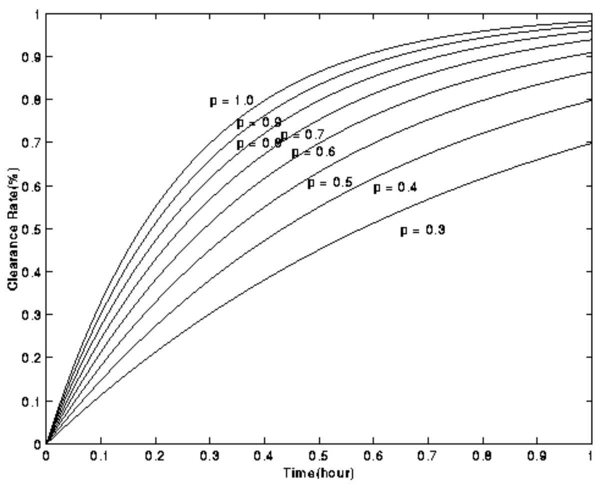

Figure 6 Effect of Detection Sensor Imperfection, 10 Robots, Same Scenario, Without Obstacles

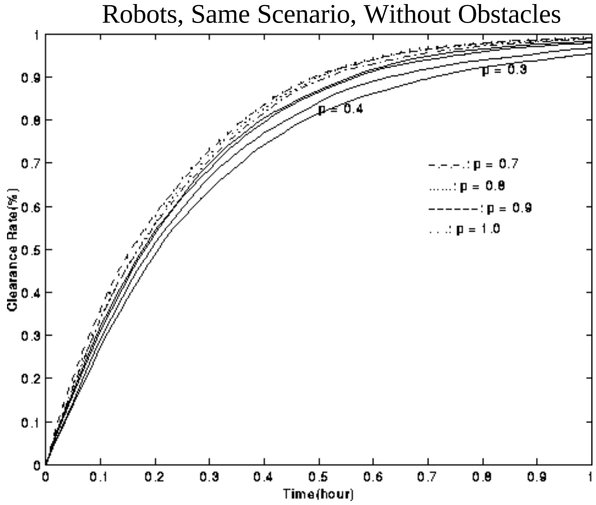

Figure 7 Effect of Detection Sensor Imperfection, 50 Robots, Same Scenario, Without Obstacles

<u>Obstacle Avoidance Delays</u>

In a field cluttered with obstacles, the obstacle avoidance maneuvering consumes extra time. Indeed, with a large number of robots also in the field obstacle avoidance on other robots as well as obstacles reduces the clearance performance to the point where no further improvement is found if the density of robots is approximately equal to the density of targets. Figure 8 with obstacles, versus Figure 6 without, shows that, in this case where the density of obstacles is also equal to the density of targets, the characteristic rate is approximately one half of that without obstacles for the same number of robots.

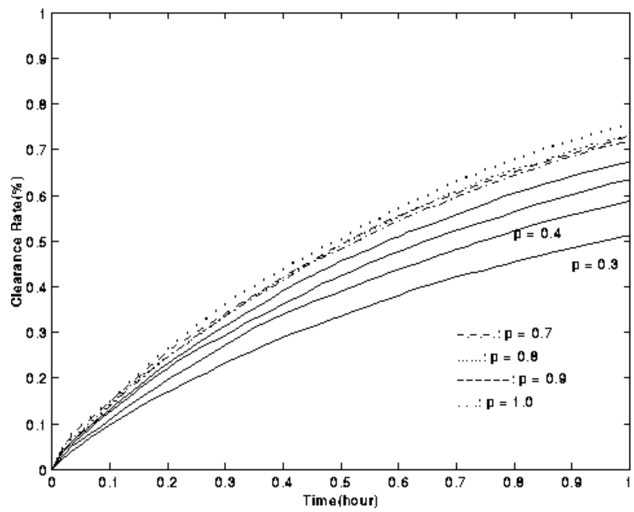

Figure 8 Influence of Imperfect Detection Together With Obstacle Avoidance - 10 Robots

<u>Probability of Casualties</u>

When using robots to pick up UXO pieces, handling qualities are not likely to be as careful as with human hands and one piece of information is the expected loss of robots in the field. This problem has been simulated under the assumption that once a detection has been registered, there will be a separately applied probability (0.2) that the robot will be destroyed. Additionally, if the robot does not detect a target within its region, *R*, there is also a 0.2 probability that it will be lost to unplanned contact with the munitions. Both of these cases contribute to a loss of robots. Results for the same scenario as simulated above give the following losses.

TABLE I

<u>Mean Robot Losses From UXO Pick Up With Varying, P 0.2 Probability of Explosion Upon Pickup</u>

P	10 Robots	20 Robots	30 Robots	40 Robots	50 Robots
1.0	8.73	12.85	14.24	14.39	14.93
0.9	8.99	12.90	14.55	13.70	14.88

0.8	8.60	13.75	15.01	14.85	14.90
0.7	8.80	13.44	14.89	14.63	15.16
0.6	8.44	13.86	14.74	15.06	15.40
0.5	8.64	13.48	14.91	16.36	14.98
0.4	8.45	13.28	15.05	15.73	15.76
0.3	8.09	13.14	15.49	16.38	17.16

While there are many statistical issues in the above, these results represent the mean losses taken over 80 simulations for each case and appear to generally conform to the idea that 20 percent of the robots are lost. The result is not unexpected, however, further work needs to be done to determine what a probability of detonation would be for each target type, and how the design and control of the pickup mechanism would be able to reduce it.

CONCLUSIONS

Studies to date indicate that clearance performance can be potentially better than currently obtained by EOD teams at the same time as provision of extra safety. Vehicle speeds must be at least 20 cm/sec in search, and higher in transit through known clear paths would be desirable. Improvements in munitions detection sensors are constantly being sought, and provided that the vehicle systems being developed can be made at very low cost, robot clearance systems could become a reality. Much more experimental work is needed.

ACKNOWLEDGMENTS

The authors wish to recognize the financial support of the NAVEODTECHDIV, Indian Head, MD., and the technical input of Dr. Gage from NRad, San Diego, as well as the valuable technical discussions with Foster Miller(Arnis Mangolds), Draper Laboratories(David Kang) and I.S Robotics(Joe Jones), Cambridge, MA.

REFERENCES

[1] O' Donnell, Freed, C. Nguyen, T., "BUGS: An Autonomous Basic UXO Gathering System Approach In Submunition And Minefield Neutralization and Countermeasures", *Proc. Autonomous Vehicles in Mine Countermeasures Symposium*, Naval Postgraduate School, Monterey, CA. April 1995.

[2] Washburn, A. R., *Search and Detection*, Arlington, VA. ORSA Books, 1989.

[3] Gage, D. W., "Randomized Search Strategies with Imperfect Sensors," *Proc. of SPIE Mobile Robots VIII Conference* (Boston), Sept. 1993.

[4] Healey, A. J., McMillan, S. M., Jenkins, D. A., McGhee, R. B., "BUGS: Basic UXO Gathering System", *Proc. Autonomous Vehicles in Mine Countermeasures Symposium*, Naval Postgraduate School, Monterey, CA. April 1995.

[5] Jenkins, D. A., "BUGS: Basic Unexploded Ordnance Gathering System Effectiveness of Small Cheap Robotics ", *MSME Thesis*, Naval Postgraduate School, Monterey, CA. June, 1995.

[6] Premier, Inc. Differential GPS Documentation.

[7] Brooks , R. 1986, "A Robust Layered Control System for a Mobile Robot", *IEEE J. Rob. and Autom.*, Vol. RA-2, No. 1.

[8] Lewis, T. A., " Simulation of Small Robotic Vehicle Performance During UXO Gathering Operations Using Discrete Event State Space Control", *MSME Thesis*, Naval Postgraduate School, Monterey, CA. Sept., 1996.

[9] Healey, A. J., Lienard, D., "Multivariable Sliding Mode Control for Autonomous Diving and Steering of Unmanned Underwater Vehicles", *IEEE Journal of Oceanic Engineering* Vol. 18, No. 3, July 1993 pp. 1-13.